An improved pattern match method with flexible mask for automatic inspection in the LCD manufacturing process

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Abstract

This research examines the electrical conductive particles of anisotropic conductive film (ACF) during the laminate manufacturing process for liquid crystal displays (LCD) and adopts an improved pattern match method to apply on-line automatic and relevant measurement inspections.

The focus of this research is describing and identifying feature images. We aim to improve the traditional pattern match methods including the gray scale designs, adaptive pattern matrix, and adaptive feature weight pattern to reduce the system function errors and to enable more efficient and quicker pattern searches and matches for full-size images.

Keywords: Anisotropic conductive film; Conductive particle; Pattern match

1. Introduction

ACF is a key material that allows LCD panels and its peripheral circuits to achieve vertical conductivity. This research adopts the hardware for machine vision and pattern identification and match technology to conduct multiple match functions on an ACF laminate test image of an LCD panel to identify the distraction and quantity of conductive particles inside each bump and to inspect and measure the movement of conductive particles after lamination.

Its purpose is to inspect and measure the movement of ACF conductive particles and ensure the correct position of the ACF particle layer with chip mark and ITO glass substrate with cell mark and to calculate whether the movement is within the allowable range. As we can see in Fig. 1, the measurement principle looks for the central point of a cell mark and bump center of conductive particle distribution to calculate the horizontal \( \Delta X \) movement and vertical \( \Delta Y \) shifting.

Fig. 2 shows the definition of the pattern match system. Discrepancy of test image and objective pattern is \( D_{\text{dis}} \). The pattern match algorithm first defines one object image and then calculates the variants of the image information groups \( R, G, \) and \( B \) to search an identical block image. We assume there is a subdivided block that includes three pieces of surface description. \( R_i, G_i, \) and \( B_i \) represent the mean of the color space expression. In addition, \( D_t = [R_i, G_i, B_i]^T \) shows the individual description of each divided block where \( D \) is from the whole divided block; that is, \( D = [D_1, D_2, \ldots, D_n] \), where \( n \) is the number of divisions in the whole block. We assume one standard pattern block as \( D' = [D'_1, D'_2, \ldots, D'_n] \), \( D'_t = [R'_i, G'_i, B'_i]^T \).

The discrepancy relationship of each divided block image is shown in Eq. (1) to compare the differences between the standard block pattern and the moved block pattern:

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From Eq. (1), we get Eq. (2)

\[
D_{ad} = \sum_{i=1}^{n} (\Delta R_i + \Delta G_i + \Delta B_i)
\]

The definition of a flexible mask system and relevant matrix parameters can be expressed as follows:

Test image \(I(x,y)\) at the size of \(M \times N\), \(1 \leq i \leq 3\); \((I_1(x,y), I_2(x,y), I_3(x,y))\), represents the gray scales \((R, G, B)\) of the coordinate point \((x,y)\).

Objective pattern \(T_{i,j,k}(p,q)\), at the size of \(P \times Q\), \(1 \leq i \leq 3\), \(1 \leq p \leq P\), \(1 \leq q \leq Q\); \(T_{i,j,k}(p,q)\), refers to the pattern coordinate system of \((j,k)\) based on the comparative first point of the pattern; \((T_{1,j,k}(p,q), T_{2,j,k}(p,q), T_{3,j,k}(p,q))\) shows the gray scale of the coordinate point of the patterns \(R, G, B\), respectively.

The pixel of objective images has a gray scale \((R, G, B)\) of \((N_1, N_2, N_3)\) and \(n\) refers to number.

Feature weight matrix is shown as \(W(p,q)\) at the size of \(P \times Q\),

\[
W(p,q) = \begin{bmatrix}
W(1,1) & \cdots & W(1,Q) \\
\vdots & \ddots & \vdots \\
W(P,1) & \cdots & W(P,Q)
\end{bmatrix}
\]

2. Method

The improved pattern match method tries to analyze and process pattern images (Lin, Pu, Chen, & Chen, 1998; Nagasaka & Tanaka, 1992) to obtain the RGB gray scale information of a subimage in each block for further image computing. It does not need the gray scale, adapt-
able matrix selection, feature weight matrix adjustment, auto contrast and luminance adjustment and the image discrepancy end calculation of each unit block to find out the identical objective pattern image.

2.1. Set up the pattern image analysis

We assume the pattern image is the same as shown in Fig. 2a and the image feature has four internal square patterns. First, according to the scale parameter, we divide the image into $P_s \times Q_s$ blocks as shown in Fig. 2b and then use the corresponding matrix of $P_s \times Q_s$ size to record the average gray scale, $R$, $G$, and $B$, of each block, where $P_s = \frac{p \text{ scale}}{\text{unit width}}$ and unit width of block: $u_w = \frac{p}{C_16}$; or $Q_s = \frac{q \text{ scale}}{\text{unit height}}$ and unit height of block: $u_h = \frac{q}{C_17}$.

The average gray scale of the upper left of Fig. 2b is shown in the equation:

$$R : \frac{\sum_{p=0}^{u} \sum_{q=0}^{v} T_1(p, q)}{(u_w \times u_h)} \quad (3)$$

The average gray scale of the block image,

$$G : \frac{\sum_{p=0}^{u} \sum_{q=0}^{v} T_2(p, q)}{(u_w \times u_h)} \quad (4)$$

The average gray scale of the block image,

$$B : \frac{\sum_{p=0}^{u} \sum_{q=0}^{v} T_3(p, q)}{(u_w \times u_h)} \quad (5)$$

We define a matrix the size of $P_s \times Q_s$ as $M(a, b)$ to record the image information of each block and where $1 \leq i \leq 3; 0 \leq a \leq (P_s - 1); 0 \leq b \leq (Q_s - 1)$:

$$\begin{align*}
\text{For } (q = 0; q < Q; q^+ = u_h) \\
\text{For } (p = 0; p < P; p^+ = u_w)
\end{align*}$$

The average gray scale of the pattern image, $R$:

$$M_1 \left[ \left( \frac{p}{u_w}, \frac{q}{u_h} \right) \right] = \frac{\sum_{p=0}^{u} \sum_{q=0}^{v} T_1(p, q)}{(u_w \times u_h)} \quad (6)$$

The average gray scale of the pattern image, $G$:

$$M_2 \left[ \left( \frac{p}{u_w}, \frac{q}{u_h} \right) \right] = \frac{\sum_{p=0}^{u} \sum_{q=0}^{v} T_2(p, q)}{(u_w \times u_h)} \quad (7)$$

The average gray scale of the pattern image, $R$:

$$M_3 \left[ \left( \frac{p}{u_w}, \frac{q}{u_h} \right) \right] = \frac{\sum_{p=0}^{u} \sum_{q=0}^{v} T_3(p, q)}{(u_w \times u_h)} \quad (8)$$

After obtaining the information on the pattern block matrix, we assume any pixel not in the pattern image feature zone as an irrelevant value. Next, we highlight the regional feature setup of the pattern feature image and use the color red\(^1\) to show the change in weight value (presumed as 1) as shown in Fig. 2c. Fig. 2c illustrates the setup of the corresponding matrix where the matrix value is shown as $x$. When matching the block pattern image with the test image $I(x, y)$, we do not calculate the $RGB$ difference. The matrix value is shown as $w$ and during the calculation of the block pattern image discrepancy value and test image $I(x, y)$, we increase the discrepancy value by $w$ times and the rest remain unchanged.

2.2. Automatic luminance adjustment

Automatic luminance adjustment is added to optimize the dynamic adjustment luminance of the pattern image movement to the image block to suit the demands for the image pretreatment, feature selection, and contrast

$$\begin{align*}
\text{If } T_{i,j,k}(p, q) &= N_i \\
\text{Then } B_{i,j,k}(p, q) &= 0 \\
\text{If } T_{i,j,k}(p, q) &\neq N_i \\
\text{Then } B_{i,j,k}(p, q) &= I(j + p, k + q)
\end{align*}$$

$$A_{i,j,k} = \frac{1}{P \times Q - n} \left\{ \frac{1}{3} \sum_{i=1}^{n} \sum_{j=1}^{p} \sum_{k=1}^{q} B_{i,j,k}(p, q) \right\} \quad (9)$$

where $A_{i,j,k}$ represents the average gray scale of the block image ($R, G, B$) and of the initial point ($j,k$) on the test image at the size of $P \times Q$.

We define the average gray scale of the objective pattern, $AT_i$:

$$AT_i = \frac{1}{P \times Q - n} \left\{ \frac{1}{3} \sum_{i=1}^{n} \sum_{j=1}^{p} \sum_{k=1}^{q} T_i(j + p, k + q) \right\} \quad (10)$$

where $AT_i$ represents the average gray scale of the objective pattern ($R, G, B$) at the size of $P \times Q$ and $T_{i,j,k}(p, q) \neq N_i$.

Because the average gray scale of the image determines the luminance, we need to design a significant value that will change the gray scale of the match pattern to strengthen contrast accuracy and to preserve a mechanism that will not change the overall contrast because of differences in light source. As a result, we create a luminance base value $LV_i$:

$$\begin{align*}
\text{If } |AT_i - A_{i,j,k}| &> LV_i \\
\text{Then } T_i(x, y) &= (k_i A_{i,j,k} - AT_i) + T_i(xy)
\end{align*}$$

where $LV_i$ is the base value of the adjusted luminance of the test image’s average gray scale, $T_i(x, y)$ is the adjusted

\(^1\) For interpretation of color in Fig. 2, the reader is referred to the web version of this article.
gray scale of the pattern matrix, $k_i$ is the adjusted coefficient of the pattern matrix gray scale.

2.3. Automatic contrast adjustment

We added automatic contrast adjustment function to the system to optimize image contrast and process image files with high complexity (Lin, Cho, Lay, Lin, & Lin, 2006) for more suitable processes of pretreatment, feature selection, and image contrast.

The horizontal axis $x$ shown in Fig. 3 has gray scale luminance at the range of 0–255; the vertical axis $f(x)$ shows the pixel number of pattern at a relative gray scale. Gray scale has a positive relationship with the luminance of image. By using all 0–255 gray scale information, we are able to view it easily with naked eyes. Compared with the image, the sum of the absolute difference between the objective pattern is identified, we are able to observe the gray scale shows, the sharper contrast is observed.

The contrast enhancement algorithm improves the image contrast and the feature of dynamic range. If the accumulated site of gray scale is identified, we are able to assume the upper and lower limits of contrast enhancement algorithm as the maximum and minimum gray scale outside this accumulation to extend the gray scale of this image. By using all 0–255 gray scale information, we are able to view it easily with naked eyes. Compared with the dilation algorithm, this method is able to reduce the pixel number of saturated gray scale and avoid a higher gray scale of image.

General contrast enhancement is shown as

$$ C_i = \frac{S_m1 - S_m2}{S_m1 + S_m2} $$

where $S_m1$ and $S_m2$ refer to the gray scale of the maximum number of pixels in the distribution and the greater difference the gray scale shows, the sharper contrast is observed.

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General contrast enhancement is shown as

$$ I'_i(x, y) = \frac{I_i(x, y) - S_{m1}}{S_{m2} - S_{m1}} \times 255 $$

We adopt another method:

We set up a contrast base value, $CV_i$, and a scan pattern matrix to gain the gray scale luminance statistic. Next, we define the region of interest (ROI) to calculate contrast value $C_i$ by using the first one-fourth and the latter one-fourth average gray scale of the pixel accumulated numbers.

As shown in Fig. 5, the effective pixel of pattern image is $(P \times Q - n)$ and

$$ S_{i1} = \left[ \frac{\sum_{x=0}^{x_1} f(x)}{\frac{1}{4}(P \times Q - n)} \right] $$

$$ S_{i2} = \left[ \frac{\sum_{x=x_1+1}^{x_2} f(x)}{\frac{1}{4}(P \times Q - n)} \right] $$

where $x_1$ is the gray scale of the first one-fourth accumulated pixel numbers,

$$ \sum_{x=0}^{x_1} f(x) = \frac{1}{4}(P \times Q - n), $$

$x_2$ is the gray scale of the first three-fourth accumulated pixel numbers,

$$ \sum_{x=x_1+1}^{x_2} f(x) = \frac{3}{4}(P \times Q - n), $$

Then, the contrast of pattern image

$$ C_i = \frac{S_{i1} - S_{i2}}{S_{i1} + S_{i2}} $$

Likely, the contrast of test image

$$ C_t = \frac{S_{t1} - S_{t2}}{S_{t1} + S_{t2}} $$

Therefore, if the difference in the contrast values between the pattern and test image $(C_{i1} - C_{t1})$ is smaller than $CV_i$, the test image is clear and there is no need to adjust the pattern image; on the other hand, if $(C_{i1} - C_{t1})$ is greater than $CV_i$, the contrast value test image is smaller than the pattern image and we need to adjust $C_{t1}$ of the pattern image:

The contrast of the original pattern $C_{i1} = \frac{S_{i1} - S_{i2}}{S_{i1} + S_{i2}}$; the contrast of the original block image $C_{i1} = \frac{S_{i1} - S_{i2}}{S_{i1} + S_{i2}}$

If $(C_{i1} - C_{t1}) > CV_i$

Then $T_i(x, y) = \frac{T_i(x, y) - S_{i1}}{S_{i2} - S_{i1}} (S_{i2} - S_{i1}) + S_{i1}$

where $T_i(x, y)$ is the gray scale after the contrast of pattern matrix is enhanced.

2.4. Calculate deference for pattern match

The sum of the absolute difference between the objective pattern and the test block image in relative position, $D_i(j, k)$, is used to evaluate the similarity and if it is smaller than the threshold value $V_t$, then the objective pattern is similar to the test block image.

If $T_i(p, q) = N_i$
Then $d_i(p, q) = 0$
If $T_i(p, q) \neq N_i$
Then $d_{i,j,k}(p, q) = \{ ||T_i(p, q) - T_i(p, q)||\} W(p, q)$

$$ D_i(j, k) = \left\{ \sum_{i=1}^{p} \sum_{p=1}^{q} d_{i,j,k}(p, q) \right\} $$. (20)
$D_1(j,k)$ extends from the initial point coordinate $(j,k)$ on the test image to distance $P$ towards the $x$-coordinate and to distance $Q$ towards the $y$-coordinate; then, $E + RGB$ gray scale of each pixel on this block image and the objective pattern at the size of $P \times Q$ are deducted to obtain the absolute value. The sum of the absolute value is $D_1(j,k)$.

If $D_1(j,k) \leq threshold value V_1$; that is, it extends from the initial point coordinate $(j,k)$ on the test image to distance $P$ towards the $x$-coordinate and to distance $Q$ towards the $y$-coordinate, then this block image is similar to the objective pattern.

3. Application of ACF image to identification and match

The partial image for position calibration used on the actual LCD production line is shown in Fig. 4a. One block image taken from it is used as an objective pattern as shown in Fig. 4b. Position squares during lamination are shown as the four white squares, but this on-line inspection is often used for images at a larger scale. The initial match can identify the similarity of the test image block position within roughly 2.0336 s.

Thus, we need to set up and analyze the objective image. First, we acquire an average RGB scale via Eqs. (3)–(5) and then from Eqs. (6)–(8), we obtain the matrix at the size of $P_s \times Q_s, M_{[a,b]}$. Because the background of this test image is complicated (Lin, Wu, Lay, & Chang, 2001), we add a green irrelevant gray block as shown in Fig. 5a. This pattern searching, however, requires more accurate contrast results. Therefore, we adopt a design of feature weight matrix and stress the difference on a white square block image for highlighting as shown in Fig. 5b. The final match result is shown in Fig. 6 where the initial position of the block is correctly identified and the run time is reduced to 1.9731 s.

The ACF image match algorithm often saves computing time because of the image scale and the demand for cost efficiency and production effectiveness. Therefore, we need to inspect the image screen at a larger scale (Lin, Lay, Huan, Chang, & Hwang, 2003).

Fig. 7 shows a test image at the size of $704 \times 480$ and an objective pattern at the size of $311 \times 283$ as shown in Fig. 4. Both are indicated with the unit, pixel. The average time to calculate 30 times is about 1.9947 s; when irrelevant gray matrix block is added to the objective pattern and the feature weight matrix is adjusted, the average time to calculate 30 times is shortened by 0.0504 s thereby improving the efficiency of the inspection process.
system efficacy by 2.53%. From Fig. 7, we are able to observe a shortened match time after adding the pattern image into the pattern matrix function.

Before conducting an inspection and measurement of the laminate change of the conductive particle, we need to pretreat the test image including gray scale transformation filter algorithm, low pass filter, erosion–dilation (Salembier, Brigger, Casas, & Pardas, 1996) as well as automatic digitalization to obtain the digitized image and then select any cell mark block. The equation will start from the initial point to look for marginal points and identify the maximum block of the cell mark block and its central coordinate of the square. To acquire the base bump block, we should first select the movement of the bump image to include the minimum bump block and its central coordinate point as shown in Fig. 8. Finally, from the difference of the central coordinate points of the cell mark and bump, we are able to obtain $\Delta X = 201$ (pixels) and $\Delta Y = 207$ (pixels).

4. Conclusion

This research uses pattern setup and analysis to add a matrix of miscellaneous gray scale to an adaptive one and run a miscellaneous algorithm on part of the pattern block to improve the executive efficacy of the system. In addition, the analysis and setup of the adaptive feature weight matrix is also introduced to reduce error match. In the pattern search, gradual proximity is used to adjust and determine the suitability of the searched objective pattern and multiple matches. Identification is conducted on a test image by plural block patterns and conductive particle patterns. This research uses effective pretreatment technology to reduce complicated ACF image noise and to improve the background contrast of objectives for search reliability and system match accuracy.

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References